

# Lumber value differences from reduced CT spatial resolution and simulated log sawing

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## Abstract

In the past few years, computed tomography (CT) scanning technology has been applied to the detection of internal defects in hardwood logs for the purpose of obtaining a priori information that can be used to arrive at better log sawing decisions. Because sawyers currently cannot even see the inside of a log until the log faces are revealed by sawing, there is little perceived need to obtain scan images as detailed as those obtained in medical CT imaging. Yet, CT scanner speed and the usefulness of CT data for decision-making are dependent on the spatial resolution of scans. Spatial resolution is a function of three factors: physical pixel size, scan thickness, and scan frequency (pitch). A  $3 \times 2^3$  factorial experiment was designed with two levels for each of these three factors, to test their effect on lumber values. Three hypothetical logs corresponding to three hardwood log grades were simulation-scanned, then simulation-sawed by a human operator using a modified Malcolm opening face heuristic. Log grade affected lumber value recovery as expected, although reduced spatial resolution (by doubling the pitch, thickness, and pixel size) exhibited no discernible pattern in our statistical tests for effects. Volume recovery for below grade boards was predicted very accurately by size, thickness, and pitch-size. The greatest opportunity for lumber value recovery improvement using information-augmented sawing appears to be in grade #2 logs.

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## 1. Introduction

Current log grading and sawing methods are limited by the inability of sawyers to see internal log defects until the log faces are opened. The development of nondestructive scanning and analysis methods that can accurately detect and characterize interior defects is critical to future efficiency improvements for sawmills (Occeña, 1991). The intent is to arrive at better log breakdown or sawing decisions and produce higher value and more consistent lumber. Scanning can be performed either on-line which will require pacing with sawing operations, or off-line prior to sawing which will require data storage and log tagging/tracking (Occeña et al., 1996). Technology has been developed to the point that wood defects can be seen in the interior of logs by using non-destructive imaging techniques.

A number of non-destructive log scanning methods have been studied and tested in laboratory experiments in the past 20 years. These include technologies, such as X-ray computed tomography (CT) (Benson-Cooper et al., 1982; Wagner et al., 1989; Hodges et al., 1990; Lindgren, 1991), nuclear magnetic resonance (Chang et al., 1989), ultrasonic (Han and Birkeland, 1992; Berndt et al., 1999), laser (King, 1979), optical (Lee et al., 1991), and microwave (Martin et al., 1987) imaging. Of these methods, CT has received the greatest interest for industrial log inspection because of its internal imaging capability, high penetrating power, efficiency, and resolution (Som et al., 1992). The research described in this paper refers to CT-based imaging, but is applicable to any internal imaging technique.

A major challenge in the eventual implementation of non-invasive scanning technology, such as CT has been the development of a rugged, wide-diameter, high-speed industrial scanner that can collect log data in hardwood sawmills (Schmoldt, 1996; Schmoldt et al., 1999). In 1999, InVision Technologies, Inc., a leader in aviation security, developed and tested a log scanning prototype based on its explosives detection CT scanning engine and is now working to make this technology available for hardwood sawmills (Schmoldt et al., 2000). There remain, however, poorly understood trade-offs between scanning speed and data quality, where the latter is composed of both contrast resolution and spatial resolution. The current study examines spatial resolution only, and its effect on log breakdown product value (i.e. lumber).

Conventional CT scanning is performed by transmitting a collimated X-ray beam through a log to a detector array at a particular cross-sectional location (Romans, 1995). Each slice has a cross-sectional area represented in terms of pixels, and a thickness, which together compose the volume (voxel) of the scan. Consecutive CT scans are taken along the length of the log at a specific incremental distance or pitch. The spatial resolution in which the CT scan data is collected is thus a function of physical pixel size, thickness, and pitch.

In principle, CT scanning speed can be increased by reducing the spatial resolution of the CT scan data collected. Besides speed, there will also be energy cost savings from generating fewer X-ray emissions. Because sawyers cannot currently obtain any internal log information until sawing commences and log faces are revealed, there is some question whether fine resolution scanning—similar to medical CT imaging—is

necessary for log breakdown. The question is how coarse can CT resolution be and still allow us to improve sawing decisions? The goal of this study is to conduct a preliminary investigation into the effect of CT resolution on the value of lumber produced from a log, with significant initial findings leading to further exploration of spatial resolution impacts on log sawing. The specific objective is to simulate the impact of CT resolution on lumber value by varying the determinants of resolution—physical pixel size, thickness, and pitch.

The subject of spatial resolution in CT scanning had been broached before. Grundberg and Grönlund (1991) described some methods for reducing data when scanning for internal log defects, motivated by the sizeable amounts of data generated while scanning. That study did not examine the effects of reducing data on the sawing outcome. Persson (1997) studied the impact of using wider CT slice spacing in the actual scanning operation itself on a simulated sawing outcome. In our study, we put to use the increasingly versatile tools of computer aided design and solid modeling to simulate the modification of three scan resolution factors: pixel size, pitch, and thickness. We then use the same tools to examine the effect of such modification on value, grade and volume yield by sawing simulation.

## 2. Log sawing

### 2.1. Traditional, information-limited log sawing

To produce lumber from a log, a sawing strategy needs to be selected. Two possible strategies in log sawing are maximizing volume recovery and value recovery. By using the former strategy, logs are sawn to obtain boards that have the greatest volume possible—as measured in board feet (BF). This sawing strategy is typically used by the softwood industry. In the latter strategy, logs are sawn to obtain boards that have the highest grade possible, and higher grade boards generally produce higher value boards. It should be noted that for the hardwood industry, and for European softwood sawmills, maximizing board volume is not necessarily equivalent to maximizing board value.

Two primary log-sawing patterns are live-sawing, and grade- or around-sawing. Live-sawing is used mostly in the softwood industry. It is a relatively simple one-pass method that produces a parallel cutting pattern. Grade-sawing is primarily for hardwoods. The purpose of grade-sawing is to constrain log defects into the fewest number of boards and to extract the most defect-free, high-value lumber possible.

The most significant limitation in traditional log sawing is the sawyer's inability to see internal defect locations and orientations prior to sawing. Without internal defect information, the sawyer has to rely on what is visible on the surface of the log and what becomes visible during sawing. This type of sawing is information-limited (Occeña et al., 2000b) in the sense that the sawyer only has knowledge of external indicators of internal features (e.g. defects). Based on external indicators, a 'best opening face' is chosen for the initial cut. This first cut, then, drastically constrains the remaining cuts, as they must be either parallel or perpendicular to this first cut.

The intent of cutting on the best face is to generate as many large boards as possible from what ‘appears’ to be the best part of the log. In grade sawing, the sawyer continues to cut from the best face until the grade of that face drops. Then, the log is rotated to another face and the process is repeated. This method for obtaining and using internal defect information is piecemeal, and the information is only partial at best.

## 2.2. Information-augmented log sawing

Previous studies (q.v. [Schmoltdt et al., 2000](#)) have demonstrated potential value gains that can be achieved by sawing logs under different log orientations and using different sawing methods. A tacit assumption for the eventual application of internal scanning to log sawing is that the knowledge of internal defects will lead to selection of the best sawing position and method, and therefore, will allow sawmills to realize these potential value gains. Log breakdown in this scenario is information-augmented ([Occeña et al., 2000b](#)) in the sense that the sawyer has knowledge about internal features including their type, size, and location. Nevertheless, without a log breakdown procedure that uses the internal information to optimize lumber value, the ability of the sawyer to improve value recovery is not guaranteed ([Occeña, 1992](#)).

As sawyers gain experience in sawing logs, they empirically develop rules-of-thumb to help them do a good job for logs of varying grades, sizes, and shapes. Six of these log breakdown heuristics for hardwoods were examined by [Malcolm \(1961\)](#) with respect to lumber grade yields and total value yield for different log grades. In Malcolm’s study, also cited in [Denig \(1993\)](#), a large number of logs were physically cut into lumber to obtain averages for the six heuristics across three log grades. Current computer software, however, has an ability to generate hypothetical logs ([Chen and Occeña, 1996](#)) and to simulate their breakdown by computer ([Occeña and Schmoltdt, 1996](#)). Unlike Malcolm’s study, which required the physical sawing of a large number of log specimens, a computer simulation allows the repeated sawing of the same logs with varying breakdown patterns. This enables the direct comparison of yields from different breakdown patterns applied to the same log specimen, rather than aggregating sawing results across many logs and examining averages. By knowing where internal defects are located prior to sawing, information-augmented sawing heuristics can be examined in addition to traditional information-limited heuristics that sawyers currently use. Based on prior simulation results ([Occeña et al., 2000a](#)), we consider only a single sawing heuristic in this paper as it is applied to internal information obtained by different spatial resolution log data.

## 3. Methodology

We began with three red oak logs—one each in grade #1, #2, and #3—that originated from a log database developed the by the USDA Forest Service. These data consist of shape and external bark features—the latter being indicative of internal defects. Internal defects included sound and unsound knots, holes, checks,

splits, decays, pitch, wane, which were computer-generated and embedded in the logs using the external bark and defects features as predictors. The computer-generated logs and defects were designed to map to the real log samples (Thawornwong et al., 2000). Wood grain, color, and texture are difficult to replicate in a solid model. However, the generated logs and defects were geometrically and topologically true to the real log samples from which they were modeled, provided that the bark characteristics were good predictors for the defects hidden inside the log. The external appearance of these logs is shown in Fig. 1. Fig. 2 displays complete internal defects for the three logs, creating a ‘glass log’ view much as CT imaging might provide.

### 3.1. Simulated CT scanning

A  $3 \times 2^3$  factorial experimental design was created with two levels for each of three factors—physical pixel size, scan thickness, and pitch. Three logs (one log in each log grade) were sawn for each of the eight experimental design combinations. Such factorial designs provide useful exploratory data that can indicate which factors are important and which, therefore, might require more detailed experimentation (Box et al., 1978). Because most CT scanners provide  $(2\text{--}3\text{ mm})^2$  cross-sectional resolution regardless of pitch and scan thickness, we chose to place more emphasis on varying pitch and thickness. Furthermore, scanning speed is more dependent on longitudinal scanning rates (thickness and pitch) than within-slice resolution. Given this rationale, we used  $(1.55\text{ mm})^2$  pixel size, 5 mm thickness, and adjacent scans for the original factor values (Table 1), where the chosen pixel size is currently being tested in a prototype log scanner. The modified factor values are  $(3.1\text{ mm})^2$  pixel size, 10 mm thickness, and 5 mm pitch.

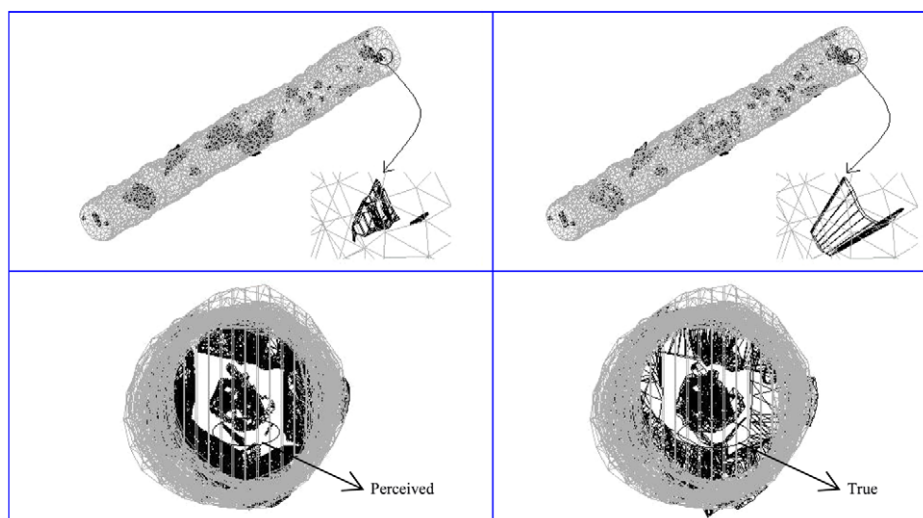


Fig. 1. Information-augmented view of the same logs as in Fig. 1.

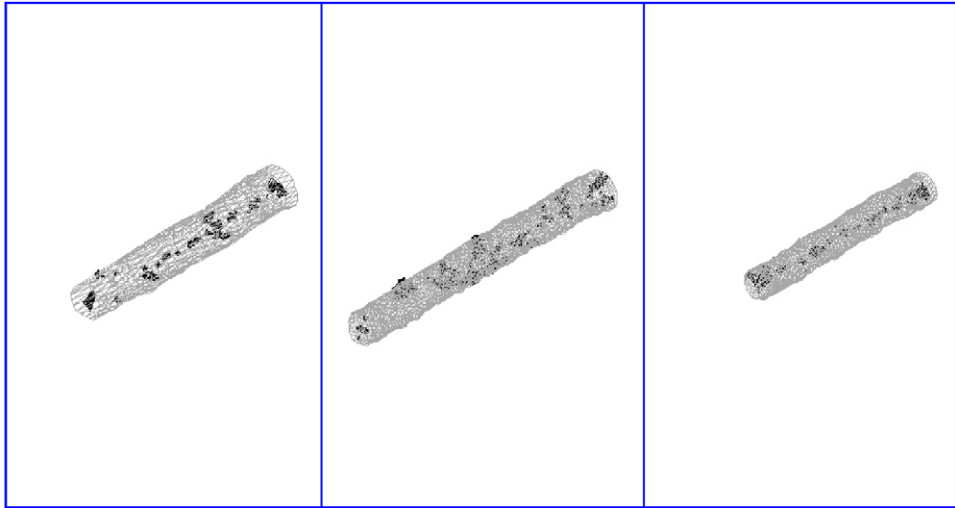


Fig. 2. Log specimens (L to R: grade #1 log, grade #2 log, grade #3 log).

Table 1

The two levels of each of three factors in the experimental design

Factor	Original value (mm)	Doubled value (mm)
Pitch	0	5
Scan thickness	5	10
Pixel size	1.55	3.1

The longitudinal position—based on simulated cross-sectional images—for simulated scan centers of successive CT scans are presented in Table 2. Examples are shown for different pitch and scan thickness values. The image location column represents an incremental scanning distance for simulating CT scans. Simulated CT scanning is broken down into three processes: data acquisition, image reconstruction, and image display.

### 3.1.1. Data acquisition

Using the GRASP sawing simulator (Occeña and Schmoldt, 1996), the original three logs were simulation sawn cross-sectionally in regions where defects existed along the length of the log—at increments of 1.25 mm as shown in Table 2. We refer to these cross-sections as ‘slices’ with no volume, as they are only cuts through the 3-D log model (Fig. 3). This 1.25 mm distance was based on prior CT data resolution used to construct the defect models and was also done to keep the number of slices computationally manageable. Each log image was then saved to collect the dimensions of defects in each cross-section.

Table 2  
Longitudinal positions (corresponding simulator images) of scan centers based on varying pitch (P) and scan thickness (T)

Image location (mm)	Scan center P = 0, T = 5	Image location (mm)	Scan center P = 0, T = 10	Image location (mm)	Scan center P = 5, T = 5	Image location (mm)	Scan center P = 5, T = 10
0		0		0		0	
1.25		1.25		1.25		1.25	
2.5	1	2.5		2.5	1	2.5	
3.75		3.75		3.75		3.75	
5		5	1	5		5	1
6.25		6.25		6.25		6.25	
7.5	2	7.5		7.5		7.5	
8.75		8.75		8.75		8.75	
10		10		10		10	
11.25		11.25		11.25		11.25	
12.5	3	12.5		12.5	2	12.5	
13.75		13.75		13.75		13.75	
15		15	2	15		15	
16.25		16.25		16.25		16.25	
17.5	4	17.5		17.5		17.5	
18.75		18.75		18.75		18.75	
20		20		20		20	2

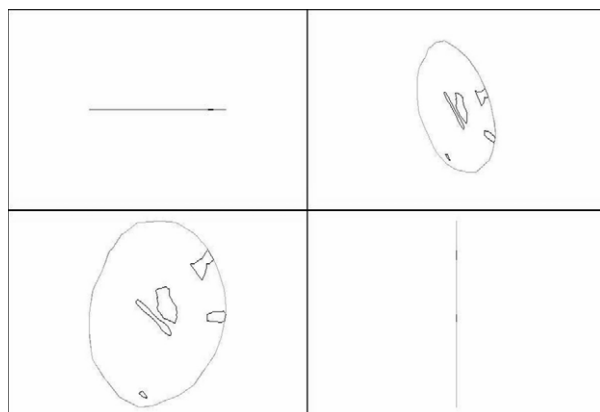


Fig. 3. Sample cross-sectional 'slice' of defects and log.

Simulated CT scanning was done primarily to capture defect images inside each log. Simulated CT images of the entire log profile were not sampled in this manner for several reasons. First, we postulate that significant cross-sectional changes in a log profile do not occur in small increments of several millimeters (Occeña et al., 1995). Second, huge sets of data will be required to capture the cross-sectional log profiles in addition to the defect profiles, which will greatly increase the computational effort required for simulated log sawing. Third, the reason for simulated CT scanning in this study is to acquire defect information inside the log to make sawing decisions. The remainder of the log is assumed to be clear wood and contains neutral information for sawing.

The sawing simulator, GRASP, performs Boolean operations on 3-D polygons describing shape, but does not have volume density information (e.g. CT numbers) for those regions. Therefore, a method was developed for averaging matching vertices of defects and to assign relative CT numbers to defect regions. First, the profile of each defect slice was redrawn with 24 circumference points ( $15^\circ$  increments from its centroid, Fig. 4). Next, the shape of all slices for the 5 or 10 mm simulated scans were combined by projecting them onto a plane by averaging the matching vertices of the defect (Fig. 5). For example, five and nine defect slices were combined to create 5 and 10 mm scan thicknesses, respectively. Finally, because not all five slices (for 5 mm simulated scans) or all nine slices (for 10 mm simulated scans) will contain the defect outline, we needed to create an averaged CT value for the simulated scan thickness. The scaling values in Table 3 were used in these cases. This scaling procedure simulates the proportional amount of X-ray energy that passes through wood and defect, and maps density measures to a geometric domain. This procedure was only required for the first and last simulated scans of each defect along the Z-axis.

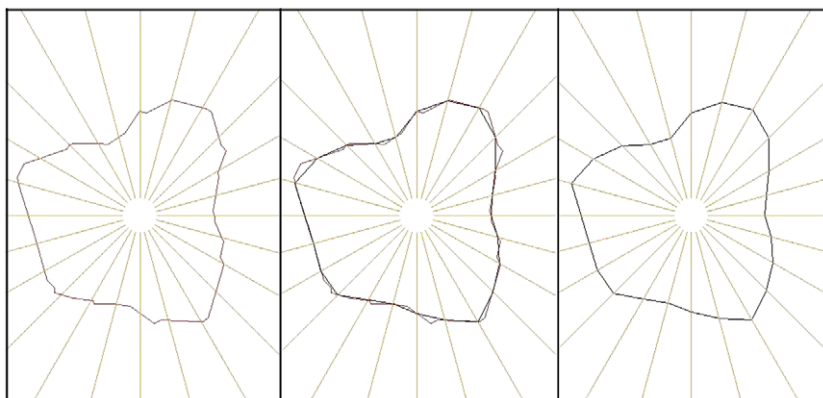


Fig. 4. An example of defect-boundary regeneration using 24 vertices (L to R: original defect slice, 24-point generation, new defect slice with 24 vertices).

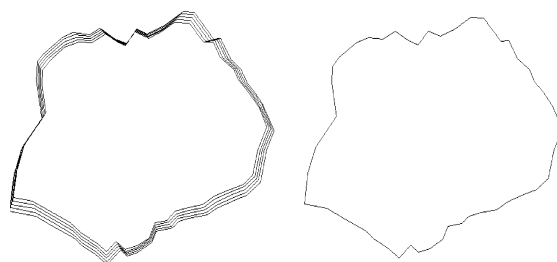


Fig. 5. The example of averaging five defect slices into one scan image (L to R: five defect slices, final averaged slice).

Table 3  
CT scaling values for 5 and 10 mm simulated scans

Scaling percentage	Number of images containing the defect	
	5 mm	10 mm
11.11	–	1
20.00	1	–
22.22	–	2
33.33	–	3
40.00	2	–
44.44	–	4
55.56	–	5
60.00	3	–
66.67	–	6
77.78	–	7
80.00	4	–
88.89	–	8
100	5	9

### 3.1.2. Image reconstruction

Since an increase in physical pixel size will result in a reduction of CT resolution, defects covering only part of a pixel were not considered in image reconstruction. Consequently, profiles were generated only from pixel values ( $1.55 \times 1.55$  mm,  $3.1 \times 3.1$  mm) that fit perfectly inside averaged slices (Fig. 6).

### 3.1.3. Image display

Slices from CT image reconstruction for each defect were combined together (Fig. 7) to create a solid model (Fig. 8). The  $2^3$  factorial design of the three parameters (scan thickness, scan pitch, scan pixel size) in Table 1 produced the equivalent of eight new instances of defect information for each original defect sample. This resulted in eight new ‘scanned logs’ in each log grade, or a total of 24 new ‘scanned logs’. We refer to the original three logs as the ‘true log set’, and the 24 logs generated from the parametric combinations as the ‘reduced-resolution set’. Because different defect types generate different CT numbers, different colors were assigned to each defect type to aid visual clarity.

## 3.2. Selected sawing technique

Twenty-seven sawing experiments were performed using an information-augmented heuristic—placing defects in the centers of quadrants, sawing the best quadrant first, and using a full taper setting (i.e. the sawline follows the outside edge of the log rather than the center Z-axis). These sawing experiments included the three original logs (true log set) and 24 generated sawing experiments (reduced-resolution set). This heuristic was selected from a previous sawing simulation study because it produced

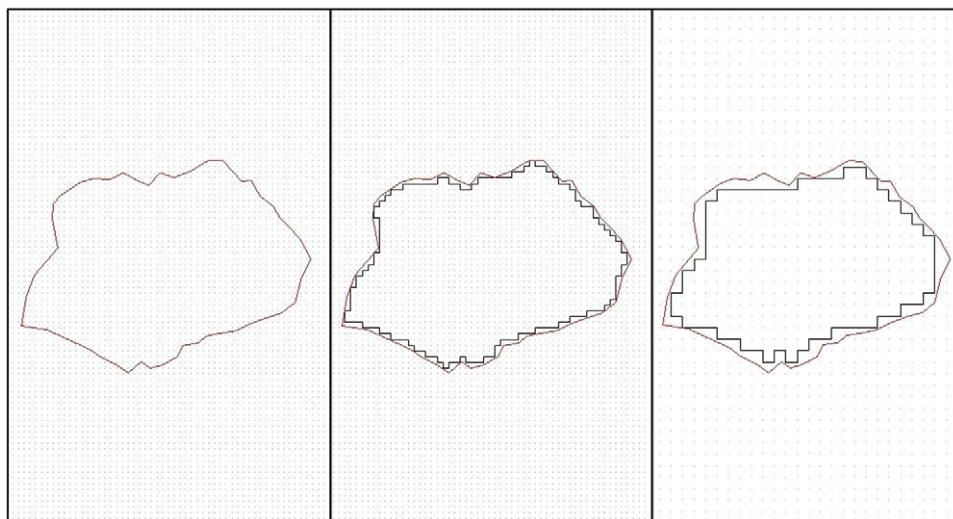


Fig. 6. An example of pixel image reconstruction (L to R: the averaged slice, 1.55 mm pixel CT slice, 3.1 mm pixel CT slice).

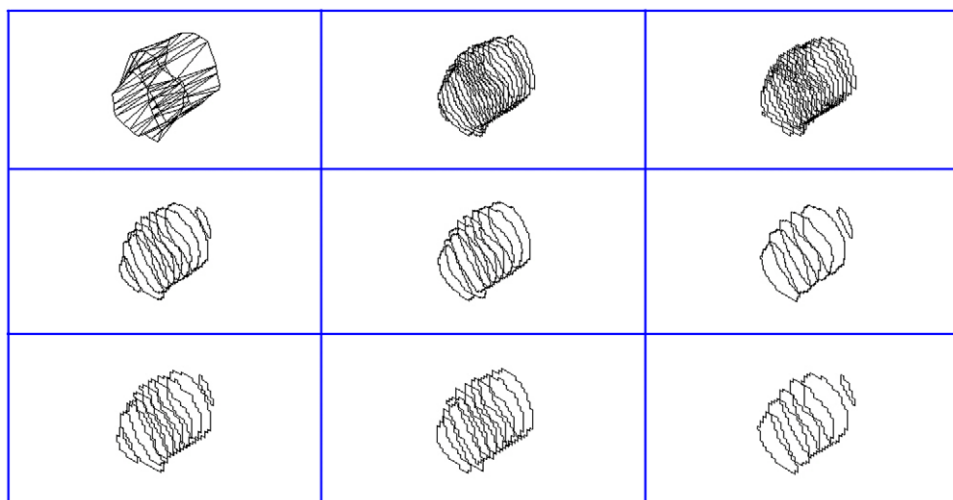


Fig. 7. An example of defect reconstruction for the  $2^3$  experimental design. (Left to right and top to bottom, original defect sample,  $P = 0$ ,  $T = 5$ ,  $S = 1.55$ ;  $P = 0$ ,  $T = 5$ ,  $S = 3.1$ ;  $P = 0$ ,  $T = 10$ ,  $S = 1.55$ ;  $P = 5$ ,  $T = 5$ ,  $S = 1.55$ ;  $P = 5$ ,  $T = 10$ ,  $S = 1.55$ ;  $P = 0$ ,  $T = 10$ ,  $S = 3.1$ ;  $P = 5$ ,  $T = 5$ ,  $S = 3.1$ ;  $P = 5$ ,  $T = 10$ ,  $S = 3.1$ ).

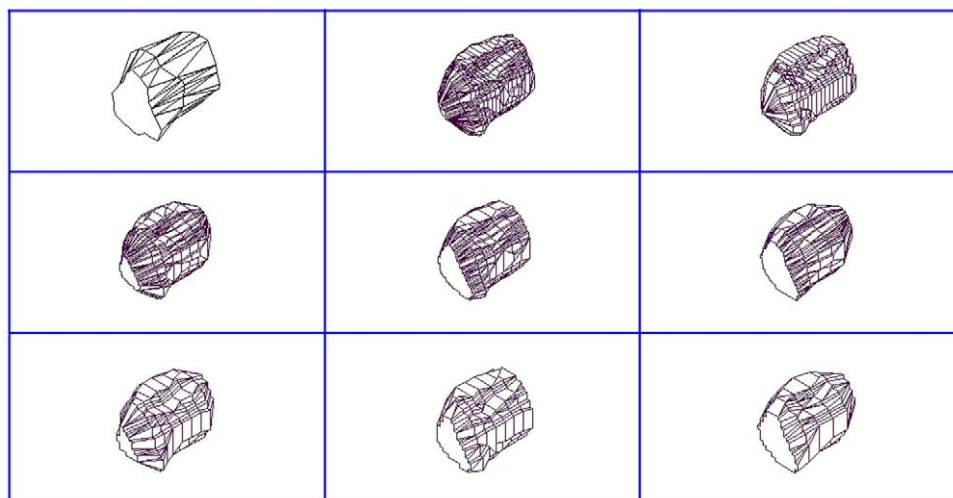


Fig. 8. Isometric views of the same defect reconstructions as in Fig. 7.

the highest value breakdown for the heuristics tested (Occeña et al., 2000a). A full description of the sawing technique is described in the following paragraph.

Each log was positioned so that major visible defects were oriented to the center of the sawing face (or quadrant). The best quadrant—which was determined by selecting the least defected quadrant of the four orthogonal quadrants used in

sawing—was set out full taper and sawn first. The full taper setting represented the total angular displacement required so that the opening face was parallel to the saw line. By using the small-end of the log as the pivot with respect to an axis perpendicular to the longitudinal axis, the log was set out so that the unopened face became parallel to the saw line. The remaining three quadrants were only taper-sawn if warranted by a potential increase in value yield. The log was not turned unless one of the other faces was judged to produce higher-grade boards, with the next quadrant selected being the least defected of the remaining unopened quadrants. This determination was made using GRASP images with all defects (internal and surface) visible. The resulting boards were edged, trimmed, and graded after the whole log had been completely sawn. For uniform comparison, logs were sawn completely, leaving no center cant.

### 3.3. *Simulation of log processing experiments*

The simulated sawing was performed interactively using the GRASP sawing simulator. The basic operations of sawing, log rotation, taper placement, opening position, and consecutive board sawing, edging and trimming, and grading have been described in [Occeña et al. \(2000b\)](#). Interactive sawing simulation differs little from real log sawing, other than the log is a three-dimensional electronic representation on a computer screen.

To arrive at the impact of ‘reduced CT spatial resolution’, the breakdown pattern for the 24 logs in the reduced-resolution set were prescribed from a visual examination of the reduced data set, but were then actually applied to their corresponding ‘original log’ in the true log set. In the GRASP simulator, there is a capability to precisely indicate a sawing pattern using line markers, without actually performing a log breakdown. These line markers can then be used as a template to perform simulated sawing of the corresponding ‘original log’ in the true log set. The above procedure is based on the premise that a ‘reduced CT spatial resolution’ image will lead to a misperception of the ‘true log’ condition, e.g. sawing a clear face where in reality there are defects hidden from view due to the reduced resolution. Sawing the corresponding log from the true log set realizes the impact of the misperception.

To avoid a learning bias from repeatedly sawing comparable logs in the reduced resolution set, the following steps were used. First, 15 additional logs, five logs in each of the three log grades, were randomly included during the prescription of the line markers, giving a total population of 42 logs. Interleaving other logs into the sawing experiments helped to break any learned log and defect patterns potentially developed for the test set. Second, presentation order for the 42 logs was randomized, and the logs were renamed to hide their identities. This was done without the sawyer’s involvement. Third, the sawyer then prescribed sawing patterns for the renamed 42 logs using line markers and the information-augmented heuristic described earlier. Fourth, sawing patterns for the 27 logs from the reduced resolution and true log sets were extracted from the total population, and simulated-sawn on their corresponding original logs in the true log set. Only after the simulated sawing were the true identities of the logs divulged to the sawyer.

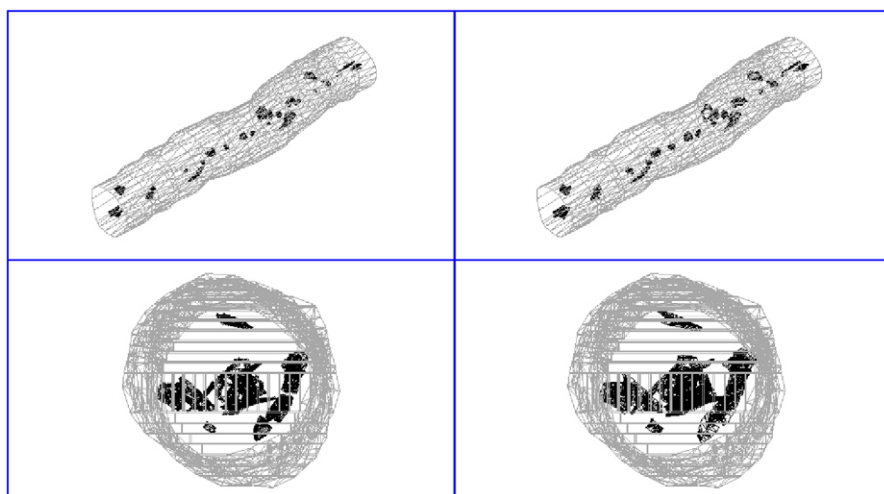


Fig. 9. Sample results from grade #1 log (L to R, top:  $P = 5$ ,  $T = 10$ ,  $S = 3.1$  reduced resolution, true defect information; bottom: perceived sawing decision, sawing pattern superimposed on true grade #1 log).

Sample results for grade #1, #2 and #3 logs are presented in Figs. 9–11, respectively. The left side of each figure shows the perceived CT resolution and sawing pattern, and the right side shows the corresponding true log resolution and superimposed sawing pattern (from the reduced resolution set). The top images in Figs. 10 and 11 show sample perceived defects from the reduced-resolution set

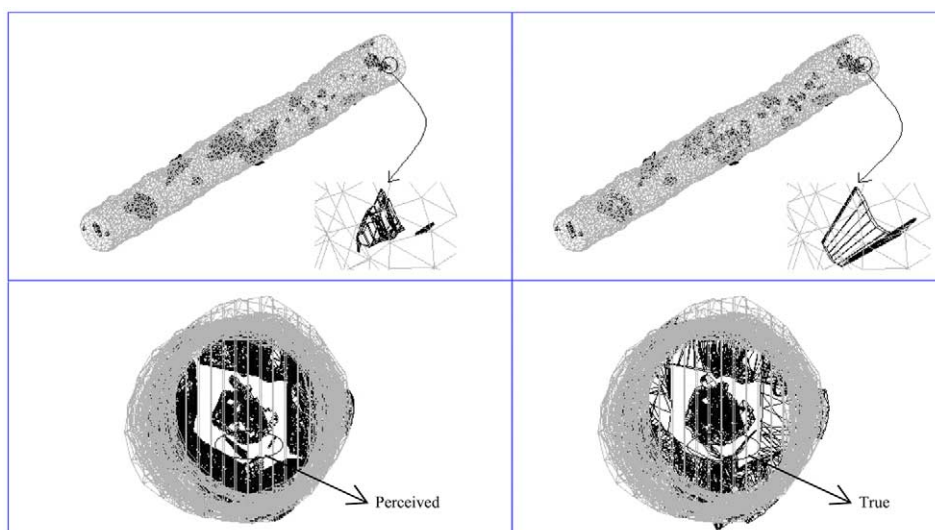


Fig. 10. Sample results of grade #2 log (L to R, top:  $P = 5$ ,  $T = 10$ ,  $S = 3.1$  reduced-resolution, true defect information; bottom: perceived sawing decision, sawing pattern superimposed on true grade #2 log).

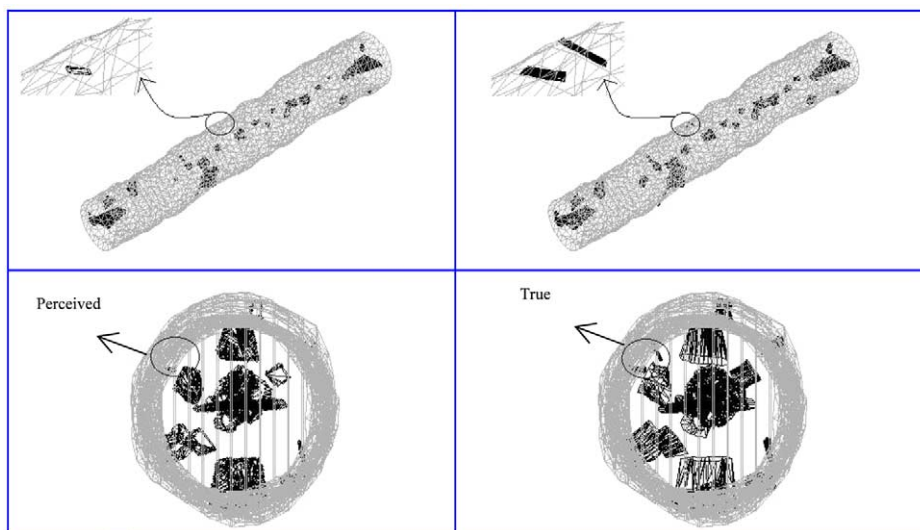


Fig. 11. Sample results of grade #3 log (L to R, top:  $P = 5$ ,  $T = 10$ ,  $S = 3.1$  reduced-resolution, true defect information; bottom (LB to RB: perceived sawing decision, sawing pattern superimposed on true grade #3 log).

compared with the actual defects and the corresponding log in the true log set. In some cases, defects are drastically misrepresented in the reduced-resolution set. The impact of these misrepresentations are quantified in the following section as we compare lumber yields for the different sawing experiments.

## 4. Results

### 4.1. Lumber value yields

After performing all 27 simulated sawings—for the three logs in the ‘true log set’ and for the 24 logs in the reduced-resolution set—the lumber values, presented in Table 4, were obtained. The highest lumber values produced from grades #1, #2, and #3 are highlighted in their respective columns. Combined lumber values of all three grades for each resolution combination appear in the last column. The true log set obtained the lowest total lumber value. Among the reduced-resolution scenarios,  $P = 5$ ,  $T = 5$ ,  $S = 3.1$  produced the highest total lumber value and  $P = 0$ ,  $T = 10$ ,  $S = 1.55$  produced the lowest total lumber value. Despite these obvious numerical differences, one might ask whether these values are truly different. After normalizing the data within each log grade (by dividing by the smallest yield), a one-tailed, pairwise  $t$ -test suggests that only the highest reduced-resolution scenario yields might be statistically different from the true log set yields ( $\alpha < 0.07$ ). A probability plot of the data on total lumber value yield (Fig. 12) corroborates this difference, and

Table 4

Lumber values obtained for each CT resolution and each log grade

Reduced resolution sets: CT factor value (mm)			Dollar value (\$\$)			
Pitch	Thickness	Pixel	Grade #1	Grade #2	Grade #3	Total
0	5	1.55	125.13	81.68	54.58	261.39
0	5	3.1	124.26	81.68	53.74	259.68
0	10	1.55	119.29	79.79	56.50	255.58
0	10	3.1	122.19	77.76	57.95	257.90
5	5	1.55	121.95	76.86	58.06	256.87
5	5	3.1	122.16	87.26	56.85	266.27
5	10	1.55	120.36	81.17	56.85	258.38
5	10	3.1	120.97	78.24	56.85	256.06
Average			122.04	80.56	56.42	259.02
Sample variance			3.72	10.75	2.31	
True log set			118.32	80.50	55.55	254.37

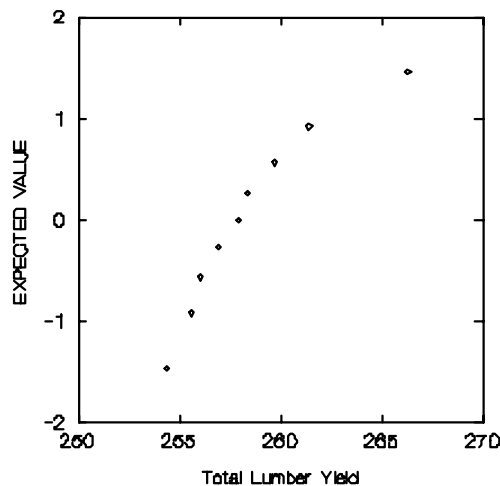


Fig. 12. A probability plot of total lumber value yield suggests that the highest value recovery scenario is an outlier, and therefore, may be different from the other yields.

suggests that this high yield scenario may be an outlier from the remaining population of yield values.

More detailed analyses examined contributions by the different spatial resolution factors (only the reduced-resolution scenarios). Tests for unequal variances indicate that there is more variation in values obtained for log grade #2 than grade #1 ( $\alpha = 0.09$ ) or grade #3 ( $\alpha < 0.03$ ). This suggests that the resolution factors chosen behave differently for different log grades. If we examine correlation of yield across the three log grades, we obtain 0.23,  $-0.63$ , and  $-0.38$  for #1/#2, #1/#3, and #2/#3, respectively. Only the negative correlation between grade #1 and grade #3 is

significant ( $\alpha < 0.10$ ), however, indicating that scenarios doing well on grade #1 tend not to do well on grade #3. Furthermore, tests for effects (using higher-level terms, e.g.  $P \times T$ , for estimating model error  $\varepsilon$ ) suggest that log grade is the only significant factor in predicting lumber value yield:

$$Y = \beta_0 + \beta_1 P + \beta_2 S + \beta_3 T + \beta_4 G + \varepsilon \quad (1)$$

where  $P$  (pitch),  $S$  (pixel size),  $T$  (scan thickness), and  $Y$  (lumber value yield) are quantitative variables and  $G$  (log grade) is a categorical variable (Box et al., 1978). Tests for mean differences between the grades were highly significant ( $\alpha < 0.0005$ ), as one would expect. The coefficients for  $P$ ,  $S$ , and  $T$  in this model were not significantly different from zero and consequently do not affect lumber yield. In addition, individual tests for interaction terms identified no significant combinations of the resolution factors.

#### 4.2. Lumber grade yields

Distributions of lumber grades—FAS, F1F, #1 Common, #2 Common, #3 Common, and Below Grade—were also examined. Volume distributions for the combined log grades and each sawing decision are provided in Table 5. The true log set obtained the highest total board foot volume. The  $P = 5$ ,  $T = 5$ ,  $S = 3.1$  reduced-resolution set provided the highest total board foot volume that can be produced from simulated CT scanning (it also produced the highest value, above). On the other hand, the  $P = 5$ ,  $T = 10$ ,  $S = 1.55$  reduced-resolution set produced the lowest total volume. These total volume yields do not seem very different, and  $t$ -test and probability plots do not contradict that inference. Of more interest is how the resolution factors affected yield of very high and very low grade lumber. Because FAS and F1F grade lumber are very similar, their yield values were combined, and the following model (Eq. (2)) was used. Again, higher order terms were used for estimating the model's error term.

$$Y = \beta_0 + \beta_1 P + \beta_2 S + \beta_3 T + \varepsilon \quad (2)$$

where  $P$ ,  $S$ , and  $T$  are defined as above and  $Y$  is board foot volume yield. None of the coefficients were found to be significantly different from zero, except  $\beta_0$ . For yields in below grade lumber, however, the following model was found to be very significant ( $\alpha = 0.01$ ) with an adjusted  $R^2$  of .938.

$$Y_{BG} = 9.81 + 2.31S + (-0.22T) + (-0.34PS) + \varepsilon \quad (3)$$

As pixel size increases the volume of below grade lumber increases, and as scan thickness increases the volume of below grade lumber decreases. In addition, there is an interaction between pitch and size that decreases below grade yields. Without this pitch-size interaction term, the coefficient for pitch is significant, but the linear model does not predict as well. Consequently, this interaction term may be an anomaly, wherein pitch by itself is a more accurate depiction of the pitch component of resolution.

Table 5  
Lumber volume yields (in BF) obtained for each CT resolution (all three log grades combined) are tabulated for each lumber grade (including below grade, BG)

Reduced resolution sets: CT factor value (mm)			Volume yield (BF)						
Pitch	Thickness	Pixel	FAS	F1F	#1C	#2C	#3C	BG	Total
0	5	1.55	12.83	44.52	148.98	113.28	36.69	11.83	368.13
0	5	3.1	0	56.40	141.25	119.73	32.56	16.18	366.13
0	10	1.55	0	57.27	151.13	94.20	52.52	11.67	366.78
0	10	3.1	0	62.72	134.52	108.13	49.03	14.48	368.88
5	5	1.55	0	62.17	136.73	103.81	52.89	11.77	367.37
5	5	3.1	0	61.78	161.93	97.89	34.79	12.69	369.09
5	10	1.55	0	62.25	142.17	115.96	31.34	10.45	362.17
5	10	3.1	0	62.28	123.42	131.65	36.10	11.50	364.95
True log set			0	34.18	157.05	133.83	35.15	11.03	371.23

## 5. Discussion

By examining [Table 5](#) more closely, we can see why the true log set obtained a total dollar value that was less than the reduced resolution sets. The true log set produced very few FAS and F1F grade boards, with a large percentage of volume in #2 Common lumber. That is, the low value of the true log set breakdown is due to a shift to lower-value board grades. These results contradict the supposition that higher CT resolution will result in higher yields. The true log set was expected to provide the highest total dollar value possible in the experiment because it expressed internal defects most accurately.

After all sawing experiments had been performed, the reduced-resolution sawing patterns were examined. This was done primarily to compare the images created from varying defect information. Defects in these images appeared to be shrunk from the true log set. This can be explained by our use of volume averaging, wherein smaller defects were more likely to have missing defect information. In fact, one heart check in the grade #2 log and two sound knots in the grade #3 log were poorly detected under the  $(3.1 \text{ mm})^2$  pixel size which, in turn, drastically reduced their sizes and changed their shapes. The circles inscribed in [Figs. 10 and 11](#) illustrate differences between perceived and actual CT images of these defects.

Nevertheless, all major defects in all of three log grades were adequately detected by the simulated CT scans for all combinations of resolution factors. It may be for this reason that, in spite of the random ordering and seeding of logs, sawing decisions for the same log grade provided almost identical sawing patterns—with some small variation coming from millimeter changes in saw blade positioning. Consequently, the advantage of complete internal defect information was not fully realized in the case of the true log set.

The logs in grades #2 and #3 produced live-sawing patterns (all parallel board cuts). Because these logs contained an abundance of defects, there was no obvious advantage to sawing on other quadrants to maximize board value. Furthermore, we noted that the edging operations varied, while the sawing patterns were almost identical. Therefore, some of the lumber value results are due to differences in edging.

While there was only one sawing solution for each log in the true log set, there were many sawing experiments involving the reduced resolution sets. These additional opportunities to find other, higher-value sawing patterns may have contributed to the increased value yield of reduced-resolution scenarios.

## 6. Conclusions

Owing to the limited number of logs used in this study (one in each grade), conclusions must be drawn cautiously. This, however, is the essence of factorial experimental designs, where one is looking for initial tendencies that can be explored in more detail with subsequent studies. The fact that our data showed no consistent influence on lumber value yield arising from pitch, thickness, and size suggests that

the ranges of values for these factors examined here may not really matter. Other values for these factors will eventually affect yield obviously, as many defects will be lost with very large resolutions. In effect, then, one can use relatively coarse scanning (5 mm pitch, 5 mm thickness, and 3.1 mm pixels) without any significant loss of value yield over finer resolutions.

With regard to lumber volume yield, the data are more specific and reliable. In particular, by increasing scanning pitch and thickness one can reduce the volume of below grade lumber. Increasing pixel size, on the other hand, increases the volume of below grade lumber. There is some interaction between size and pitch, so that for certain combinations of those factors increases in below grade lumber are more than offset by increases in higher value lumber (F1F and #1 Common grades).

There is some evidence that points to grade #2 logs as critical to value improvements using internal defect information. First, the grade #2 log exhibited significantly higher variability in value yields across scanning scenarios versus the other two grades. Second, the scanning scenario that produced the highest yield also did the best on the grade #2 log. Third, it seems intuitively reasonable to expect that high-quality logs can be sawn for high yield relatively easily, owing to their low numbers of defects. Conversely, lower grade logs possess very little opportunity for large value improvements using internal defect information, stemming from their lack of large clear wood areas. If this trend is borne out following additional sawing studies, then it means that log scanning can be tailored to log grade, using lower resolutions for grades #1 and #3 and higher resolutions for grade #2. Even still, it may also be possible to increase value yield recovery for grade #1 and #3 logs that have atypical shape or defect patterns.

Edging and trimming operations are known to be a potential source of recovery improvement for sawmills. Even though the resulting board from these logs were consistently edged and trimmed by the simulator, there was no attempt to perform these operations optimally. One of us (Schmoldt) is currently developing an algorithm for optimal edging and trimming. It would be useful to include such a module into the simulator to remove any errors associated with sub-maximal edging and trimming.

Having now established this experimental methodology, it is less difficult to expand the results with data from other logs. The addition of data from several additional logs in each grade will allow us to expand and/or verify the results generated here. Determination of lumber value is the combined effect of volume and grade for each board sawn. This suggests that additional data may not illuminate any greater detail about scanning resolution impacts on value. Volume recovery is obtained more directly, however, and was explicitly related to spatial resolution in this study.

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